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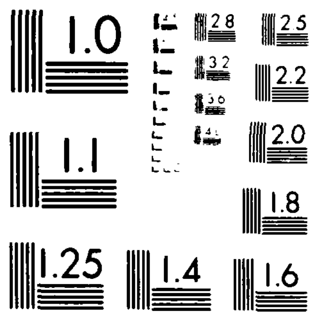
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THE SUBJECTIVE TRANSFER FUNCTION APPROACH FOR ANALYZING SYSTEMS

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PREFACE

This paper describes the Subjective Transfer Function (STF) approach to analyzing systems that was developed during research on evaluating the contribution of command and control to the overall combat effectiveness of tactical air forces. The purpose of the paper is to explain the advantages of using the STF approach over other commonly used approaches in terms of developing causal system models, and to detail the steps involved in its use in situations where hard (equipment), soft (procedures) and human elements all have main effects on outcomes.

THE SUBJECTIVE TRANSFER FUNCTION APPROACH FOR ANALYZING SYSTEMS

The subjective transfer function (STF) approach was developed for analyzing complex systems where many variables either directly or indirectly impact on system outcomes. The idea is to test hypotheses about how "experts" perceive their system to function. Hypotheses are algebraic functions (STFs) that specify how factors comprising the system affect judged outcomes. Once the STFs are known for all groups of system experts, they can be used to evaluate how changes in system inputs affect outcomes. We detail the steps involved in the STF approach, discuss its measurement basis, and provide illustrations from research in tactical Air Force command and control.

Based on research for Project AIR FORCE (See Refs. 37-39), with additional support from The Rand Corporation. The authors thank Barbara Rose for her research contributions.

1. INTRODUCTION

The Subjective Transfer Function (STF) approach is a subjective measurement method for analyzing complex systems where many factors either directly or indirectly impact on system outcomes (37). In this approach, systems are analyzed from the perspective of the "expert," who by definition knows and understands the system. The expert judges what outcomes would result from different descriptions of system capabilities. The measurement problem is one of constructing these descriptions from experimental designs that allow effects of the information contained in the descriptions on judged outcomes to be measured. The algebraic modeling approach to subjective measurement provides this capability. This approach is the measurement basis of the STF approach.

In this paper, we first discuss the features of the algebraic modeling approach and describe how these features provide resolutions to measurement problems found with other commonly used approaches. Then we describe how the STF approach incorporates basic features of the algebraic modeling approach and provides additional features to handle complex systems. We use examples from research in tactical air command and control to illustrate the steps involved in applying the STF approach.

II. THE ALGEBRAIC MODELING APPROACH AND ITS ADVANTAGES

The algebraic modeling approach to subjective measurement includes functional measurement (2, 3, 4) conjoint measurement (20, 21), and the principle of stimulus scale convergence and scale-free tests (5, 13, 14), which are important tools of model analysis. A discussion of the basic ideas of the algebraic modeling approach can be facilitated by breaking up judgments into three parts. First, stimuli are transformed to their subjective counterparts. For two stimuli, S(i) and S(j), this conversion process can be written

$$s_i = H(S_i) \qquad (1)$$

and

$$s_j = H(S_j),$$

where H is the transformation function (referred to the psychophysical function or utility curve), and s(i) and s(j) are the subjective scale values. Second, subjective scales values are combined into a subjective response, r, by the combination function, C:

$$r = C(s_i, s_j). \qquad (2)$$

Third, the subjective response is transformed into an overt response, R, by the judgment function, J.

$$R = J(r). \tag{3}$$

In the algebraic modeling approach, the idea is to design experiments that provide stringtent tests of the hypothesized combination function, C. Once the unique predictions of an hypothesized function are supported by the data, the subjective values (s and r in the above equations) are known; they are the least-squares estimates of the function. Thus in this approach, the validity of the subjective measures rests on the validity of the combination function, C. If an hypothesized function model does not pass stringent tests of its unique predictions, then both the function and its scale values are rejected.

Carefully constructed experimental designs are required to adequately test among the unique predictions of the functions under consideration. A detailed discussion of these designs is beyond the scope of this paper. Examples of factorial combinations of stimuli that allow tests betwen the predictions of additive and interactive functions can be found in Anderson (4), Birnbaum and Veit (13), and Levin (16). Descriptions of different predictions of polynomial functions can be found in Krantz et al. (20); examples of the scale-free design that allows a test of the linearity of J in Eq. 2 can be found in Birnbaum (5), Birnbaum and Veit (14), and Veit, Rose, and Ware (40). Birnbaum (6) and Norman (24) discuss some problems and resolutions involved in testing weighted functions that contain a weight and scale value product (for example, the multiple regression model or an averaging model such as the multi-attribute utility function). Examples of experimental designs that allow tests of the predictions of these functions can be found in Birnbaum (6), Birnbaum and Stegner (11, 12), and Veit, Callero, and Rose (38).

A major problem with some subjective measurement approaches is that they do not employ proper experimental designs--those that allow tests of the assumed function's predictions. Thus, conclusions about effects of factors and subjective scale values are highly suspect. Two commonly used approaches that fall into this category are discussed next.

USING 'DIRECT' SCALES AND ASSUMED MODELS

Many researchers using the multiple regression or multi-attribute utility theory function assume the validity of their function as the appropriate combination function (C), as well as the validity of the weights and scale values they use to compute the function. Neither assumption can be tested using their experimental designs.

Subjective measures of weights and scale values are generally obtained using "direct" scaling techniques (31, 32). In the direct approach, scales of "sensation" are obtained by having respondents assign numbers to stimulus descriptions according to instructions. Many operational definitions have been proposed for obtaining direct scales (for example, the category rating and magnitude estimation scales recommended by Gardiner and Edwards (17) for obtaining scales for the subjective expected utility model). However, different operational definitions of the same stimuli produce different "scales." Further, scale values depend on features of the experimental design, for example, the range and spacing of the stimuli and the response scale. More importantly, psychologists have severely questioned the scientific meaningfulness of "scale values" obtained from operational definitions

(9, 13, 19, 29, 30, 34, 35). Despite the lack of a testable basis for conclusions, many people interested in obtaining subjective measures for a wide variety of reasons (e.g., analyzing systems) use and recommend these procedures (see as examples, 17, 18, 25, 22, 26, and the PATTERN technique described in Waddington (41)).

SAATY'S APPROACH

Saaty (28) proposes another approach to obtain subjective measures that is also fraught with measurement problems: his ratio model is not adequately tested and therefore his scale values are suspect, and he doesn't provide any assessment of his aggregation model.

Saaty proposes that a ratio model underlies category ratings of ratios. This is a testable proposition using the factorial design of stimulus cues that he describes (given that the respondent and not the experimenter fills in the entire matrix). However, the appropriate test of the model is not the goodness-of-fit index he recommends. Indices of fit can be high when deviations are significant and systematic. A way for both the researcher and the reader to assess the fit of a ratio model is to see graphs of the data. When responses are plotted as a function of the levels of one factor with a separate curve for each level of the other factor, the resulting curves should form a bilinear fan; deviations from the bilinear prediction of the model (which can be obtained from the analysis of variance) should be nonsignificant (2, 13, 35). We have graphed the data presented in Saaty (28) and have found them to be considerably different in form than the ratio model's predictions. If the model does not account for the data, what meaning can be attributed to the scale values derived from the model?

Further, suppose a ratio model did account for overt responses, that is, deviations from bilinearity were nonsignificant. There is a body of literature (7, 8, 10, 35, 36) that suggests that respondents take differences when instructed to take ratios and then take an exponential transformation of the differences. That is, when respondents are instructed to make ratio judgments, the combination rule (C in Eq. 2 above) is a subtractive model and J in Eq. 3 is an exponential transformation. Thus, the stimulus scale values would have to be obtained from the subtractive model after performing a logarithmic transformation on the "ratios". The scale values derived from the subtractive model would be unique to an interval scale, since any linear transformation of the scale values used in the subtractive model would reproduce the rank order of the data points in a factorial matrix. It is interesting to note that scale values derived from a ratio model are unique only to a power transformation (20). Thus, even if the more stringent designs were employed (see for example, 7, 8, and 35), that provided a test of whether C in Eq. 2 was subtractive or ratio <u>and</u> the data supported a ratio model, the scale values derived from the ratio model would only be a power transformation of the "true" values under the model; they would <u>not</u> be ratio scales as Saaty suggests. Therefore, it would be inappropriate to make ratio comparisons of the "weights" (see, for example, (1)).

SUMMARY REMARKS

The algebraic modeling approach places subjective measurement in a scientific framework in the sense of hypothesis testing and rejecting. Stimulus scales are parameters of a theoretical function that accounts for a nontrivial data array.

III. THE STF APPROACH

Complex systems are defined here as those having many sets of factors that impact on system outcomes either (a) directly or (b) indirectly by affecting outcomes internal to the system. Different groups of people are generally "expert" about different parts of the system. In the subjective transfer function (STF) approach, the effects of system factors on judged outcomes are measured for each group of experts separately. The STFs serve to bring the perceptions of all of the groups together into a cohesive whole that makes it possible to compare effects of different system capabilities on the outcomes of interest. These ideas are illustrated in this section.

Three major stages characterize the STF approach: (a) developing initial system structures, (b) testing among hypothesized STFs to explain the causal relationship between factors defining the system and the outcomes they affect, and (c) evaluating different systems defined by the same structure but that vary in their system capabilities. These three stages are discussed below.

DEVELOPING A STRUCTURE OF THE SYSTEM

A structure of the system identifies the factors and outcomes of interest. Structure development is done in conjunction with the appropriate body of system experts.

Identifying Outcomes, Factors, and Factor Levels

The first step in developing a structure is to identify the outcomes produced by the system that provide the important external measures of the system's effectiveness. This is done through interaction with those interested in the system evaluation. Then factors thought to directly affect these outcomes are identified. These factors may be outcomes that are produced within the system (referred to as suboutcomes) that are themselves affected by other system factors. These factor/outcome (suboutcome) sets, which are called experimental units, are identified through interaction with people that are expert in the areas. A hierarchical causal representation of the system develops by specifying system factors for suboutcomes until all suboutcomes are affected only by factors that represent system input characteristics or basic system features. Such factors are called "primitive factors."

A complex system that includes two experimental units is depicted in Fig. 1. This is a structure of a tactical Air Force command and control system that was investigated using the STF approach (38). In this figure, there is one external outcome measure--how well Air Force commanders can perform their immediate targeting task (pairing tactical aircraft with important enemy ground force targets in a timely manner); there is also one factor/outcome set (experimental unit 1--upper portion of the figure), and one factor/suboutcome set (experimental unit 2--lower portion of the figure). The expert group corresponding to experimental unit 1 performs the immediate targeting task. The group corresponding to experimental unit two is expert in identifying enemy targets. In the first experimental unit, six factors are hypothesized to directly impact on Immediate Targeting. In the second experimental unit, seven factors are hypothesized to impact on Immediate Targeting indirectly, through the suboutcome Target Identification. Thus, the hypothesis shown in Fig. 1 says that part of the ability to do immediate targeting depends on how well the targeteers are able to identify important enemy targets.

Simultaneous with identifying the factors, dimensions associated with factors and outcomes have to be defined. The definitions for the outcomes and factors shown in Fig. 1 are presented for each experimental unit separately in Table 1; definitions for experimental units one and two are shown in Panels A and B, respectively. (Note that outcomes define the judgment task; factors define system capabilities.) Factor levels selected for experimental manipulation should span the range from the worst to the best capability that might be expected over a given time period. This feature is important if future conditions or system characteristics are to be built into the model for evaluation purposes. Factor levels that were selected for the factors shown in Fig. 1 are presented next to each factor definition in Table 1.

The structural representation shown in Fig. 1 hypothesizes _two_ STFs. The first (T1) specifies the causal link among the six factors impacting on the immediate targeting outcome, and the second (T2) specifies the causal link among the seven factors impacting on Target Identification. These functions are referred to as _subjective_ because they are models of combination processes (C in Eq. 2) not directly observed. They are referred to as _transfer_ functions because, when their functional forms have been determined and they are being computed to evaluate a particular system, the output of one function is transferred for use (after conversion to a subjective value) as an input value to the function above it. For example, the output of T2 in Fig. 1 would identify the factor level and hence the subjective input value for Target Identification needed to compute T1. This is why it is important to identify factors that link experimental units in the same terms (note in Table 1 that immediate targeting is defined in the same terms when it is a dependent variable (experimental unit 2) and an independent variable (experimental unit 1). Examples of using STFs are presented later.

Identifying Alternative Structures

Structural alternatives refer to alternative hypotheses about the number of STF paths linking factors to outcomes. Alternative structural hypotheses arise for two reasons. The first reason concerns different hypotheses about how the expert combines information included in a description of a system's capabilities. For example, it seems reasonable to hypothesize that an immediate targeting expert (experimental unit 1 of Fig. 1) might combine information about the three factors concerning their friendly forces (Alert Forces, Airborne Forces, and Weather) separately from information about their other capabilities--Target Identification, Facility Operability, and Dissemination. The upper portion of Fig. 2 shows that this separate combination process is represented structurally by inserting an "intermediary factor"--Execution Status Information--into the structure. (An intermediary factor is not identified by factor levels because it is not manipulated in experimental designs.) This represents the hypothesis that respondents combine information about their own forces and then combine this subjective output with their values associated with Target Identification, Facility Operability, and Dissemination before making their immediate targeting judgment.

This alternative structure requires depicting two STFs (and hence two paths) for the immediate targeting experts in experimental unit 1. An alternative structural hypothesis for the Air Force targeteers (experimental unit 2 in Fig. 1) might be that they combine information about enemy emitters separately from information about enemy vehicles; then they take the values of those outputs and combine them with their value associated with the processing capability. This alternative structural hypothesis that requires 3 STFs for targeteering experts is depicted in the lower portion of Fig. 2. Thus, this entire structural alternative for these two groups of experts produces a representation with five STFs and hence five paths--two for experimental unit 1 and 3 for experimental unit 2. Other clumping hypotheses would change the number of paths and STFs. For example, the hypothesis that emitter information was not perceptually clumped but vehicle information was (or vise versa) would reduce experimental unit 2 to two 2 STFs, and the entire structure to 4 STFs.

The second reason for hypothesizing alternative structures is that too many factors define a single experimental unit. This presents a problem because the major experimental design feature needed to test judgment models (STFs) is the factorial combination of stimuli. Each cell in the factorial design translates into a questionnaire item. A fully crossed design generates questionaire items that contain as many pieces of information as factors used in the design. For example, three factors would produce a questionnaire item with three pieces of information. Our research has indicated that between five and seven pieces of information (depending on the interrelationships among the factors) are maximum for a respondent to simultaneously process. Miller (23) has estimated seven plus or minus two pieces of information to be maximum.[1]

The number of factors defining an experimental unit can be reduced by hypothesizing a subset of the factors to impact on a suboutcome that is meaningful within the framework of the evaluation goals. For example, the execution status information factor shown in Fig. 2 could be changed from an intermediary factor to a suboutcome. This would require defining the factor along a dimension that is meaningful both for the respondent group that that would judge that factor as an independent variable (the immediate targeting experts for the structure shown in Fig. 2) and the respondent group that would judge the factor as a dependent variable (this could be the same or another expert respndent group entirely). In situations where the same respondent group is expert in two experimental units, they would be asked to make judgments about their two different tasks at different times, or different subsets of the respondents would be assigned to the different experimental

[1] Questionnaire length also increases rapidly as the number of factors (and factor levels) are added to the experimental unit when factorial designs are used. Variations on completely crossed factorial designs that descrease the questionnaire length while maintaining enough constraints to adequately test among the unique predictions of the functions being considered are discussed and illustrated in Birnbaum and Stegner (12) and Veit et al. (39).

units.

Figure 1 was selected to illustrate the ideas behind developing a complex system structure and hypothesizing alternative structures because it only had two experimental units. In reality, most complex systems will be quite a bit larger. For example, a tactical Air Force command and control system researched by Rand was composed of 105 factors to be manipulated, 30 suboutcomes, and one final system outcome.

STF HYPOTHESES

Table 2 describes some algebraic functions that might be entertained as STFs at the outset of a complex system investigation. Ideas about what functions to entertain come from the judgment literature and previous research in the problem domain of interest.

The functions in Table 2 have been specified for "f" factors; i refers to the factor, and j to the factor level; w(0)and s(0) are "initial estimate" parameters--what the response would be in the absence of specific information, and r is the subjective response.[2]

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[2] The J function shown in Eq. 3 that relates subjective responses, r, to observed responses is not indicated in these equations. Its determination is discussed in literature on the scale-free design (5, 14).

The functions shown in Table 2 have both scale value (s) and weight (w) parameters. For all but the differential weight function shown in Panel B, weights are associated with factors and are constant across factor levels. The differential weight function allows a different weight (and scale value) for each factor level. The functional description "Multiplicative combination of factors" at the top of Panel B allows for a wide variety of algebraic formulations where all factors may combine multiplicatively, or two or more factors may combine multiplicatively but additively with the other factors. (An example with three factors, A, B, and C, where factors A and B combine multiplicatively but they both combine additively with C would be:

$$r = (w_1 AB + w_2 C)/(w_1 + w_2). \qquad (4)$$

Each function described in Table 2 makes a different prediction with respect to the pattern the judgment data should follow when appropriate experimental designs are used. For example, one prediction all of the functions shown in the left-hand panel have in common is that of no interactions among the factors Conversely, the functions in the right-hand panel can account for interactions among the factors. The functions within each panel make other differential predictions with respect to the judgment data.

It is important that both structural and STF hypotheses be specified in advance for each experimental unit so that experimental designs allow tests among their predictions.

IV. DETERMINING STFs AND FINAL STRUCTURE

The explanatory power of a proposed STF lies in its ability to reproduce the systematic details of the data. A good way to assess this ability is to plot predicted points and responses on the same ordinate as a function of the levels of one (or more) factor with a separate curve for each level of another factor. These predicted and obtained graph allows assessment of the magnitude and direction of the function's deviations. Statistical tests among the viable subset of structure/function combinations are made for each experimental unit using STEPIT, a parameter-estimation subroutine (15) programmed to select parameters that minimize the sum of squares discrepancies between the data and the STF's predictions. The STF with the smallest discrepancy (taking diferences in degrees of freedom into account) would be considered the "best-fit" STF for that experimental unit. However, if predicted and obtained graphs reveal that deviations are large and systematic for the statistically "best" function, that function would also be rejected as the appropriate STF. Predicted and obtained graphs provide a tool for diagnosing the pattern of the residuals (errors) and determining a "correct" function. If a new function(s) suggested by the pattern of deviations cannot be adequately tested on the available data (i.e., variations on the original experimental design are needed to adequately test its predictions), it would be necessary to redesign the experiment and collect new data.

The fit of the STFs to the data drives the structure. For example, the structure shown in the upper portion of Fig. 2 postulates that an

STF that explains the effects of Alert forces, Airborne forces, and Weather on Execution status information is embedded in an overall STF that explains the effects of the four Immediate Targeting Factors--Target Identification, Facility Operability, Execution Status Information, and Dissemination. Figure 1 postulates that immediate targeting judgments are better explained by a simpler six factor STF. If a simple six factor STF provided a good fit to the data, the immediate targeting portion of the structure would be depicted as shown in Fig. 1. Thus, the STF drives the decision on how the structure should be depicted as well as the subjective values needed to evaluate and compare systems.

V. COMPARING SYSTEMS

Once the system's structure and STFs have been determined, it is possible to compare systems that are defined by the same structure but differ in capability levels. Capabilities that are input to a system are defined in terms of the system's primitive factor levels; sytems that are different differ in at least one primitive factor level. Determining the output of a single system requires putting the subjective scale values associated with each primitive factor level defining the system into the STFs associated with the primitive factor, computing those STFs, transfering the outputs from those STFs into the STFs to which they are linked (after converting to subjective scale values), and so forth until all STFs have been computed and the final outcome measure has been obtained.

An example of this evaluation procedure is presented in this section. The structure shown in Fig. 3 is the final structure that resulted from the structural hypotheses entertained by Veit et al., (38). (Note that the difference in structure between Figs. 2 and 3 is that the intermediary factor "Execution Status" has been omitted.) The function selected as the appropriate STF is named at each path. At the top, a range model (see Table 2) best accounted for the immediate targeting experts' data. The minus sign indicates that the omega term in the range model was negative, indicating overall divergent interactions among the 6 factors in this experimental unit. The interpretation of the divergent interactions is that the better the capability that the immediate targeting expert has to work with on one factor, the more of a difference it makes how good their capabilities are on the other factors. A range model with a positive omega term best accounted for the targeteers data at the target identification path. The convergent interaction found here indicated that the more the targeteers knew about enemy emitters, the less of a difference it made about how much information they had on enemy vehicles (and vise versa). (Better capabilities, however, always received a higher judgment). The two intermediary factors, Vehicles and Emitters, hypothesized in Fig. 2 were retained. At the vehicle path, the range model with a negative omega term best accounted for overall divergent interactions found among these three factors. The relative weight function with an initial impression (the third function shown in Table 2A) best accounted for the emitter data; that is, the overriding trend in these data was independence among the factors on the target identification judgments.

Suppose it was of interest to compare three different systems described by the structure shown in Fig. 3 on how well the immediate targeting people thought they could do their job (the percent force application opportunities they thought they could exploit). As stated earlier, a particular system is identified by its primitive factor levels. The primitive factors in the structure shown in Fig. 3 are the location/classification, coverage, and currency factors associated with vehicles; the location, coverage and currencey factors associated with enemy emitters; Processing; Facility operability; Alert forces; Airborne forces; Weather; and Dissemination. (Definitions of these factors were presented in Table 1.) Three different systems are shown in Figs. 4-6. The circled primitive factor levels identify their differences. The first thing that is needed for an evaluation of these systems is the subjective values associated with these levels.

We will describe how subjective values are obtained for primitive factor levels and how STFs are computed using the factors and range model at the vehicle path shown in Fig. 4. For this path, subjective values associated with a currency level of 30 minutes, a coverage level of 40% and a location/classification level of "Clr.wx. loc" (can locate and classify enemy vehicles in clear weather only) are needed to compute the range model. In Figs. 7A-7C, subjective scale values are plotted as a function of the factor levels for Vehicle Location/Classification, Vehicle Coverage, and Vehicle Currency, respectively;[1] the range model for the vehicle path is written at the top of Fig. 7. For Figs. 7B and 7C, the resulting curves represent the psychophysical functions (utility curves) for these factors (H in Eq. 1). The subjective scale value associated with a currency level of 30 minutes is shown by the connecting dashed line in 7C. When factors are defined along a physical continuum (e.g., time, percent, distance), it is possible to estimate scale values of factor levels not previously identified or manipulated by projecting from the psychophysical function. This is demonstrated for the 40% coverage value in Fig. 7B. When factor levels are written descriptions such as the location/classification factor (Fig. 7A), scale values are obtained only for the descriptions used in the experiment. The scale value needed for the system described in Fig. 4 is indicated on the graph. If a <u>different</u> written description (one not used in the

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[1] Recall that, when the STF has been determined, the parameter values are known; they are the least-squares estimates of the function.

experiment) is used to define a primitive factor level, it has to be scaled in a new experiment for its experimental unit, since a curve cannot be drawn to connect scale values associated with written descriptions. The subjective values shown in Fig. 7 and the other parameters of the range function would be aggregated as specified by the function to obtain the output of the intermediary vehicle factor. This output is used in the range model with a positive omega coefficient at the immediate targeting path. This process is repeated for each STF, starting at the primitive component levels and proceeding to the top (immediate targeting output).

For the particular system shown in Fig. 4, the theoretical prediction is that 33% of the important targets would be identified, which leads to a theoretical prediction that about 48% of the important immediate targeting opportunities would be exploited. Figure 5 shows that increasing the targeteers' ability to identify targets to 68% (by changing the systems' capabilities as indicated by the circled primitive factor levels) increases the ability to do immediate targeting to only 52%, keeping the other capabilities for this upper portion of the structure the same as in Fig. 4.[2] In Fig. 6, the primitive factor levels for the lower portion of the structure are the same as in Fig. 4, but the immediate targeting capabilities have been greatly improved in several areas (Alert Forces, Airborne Forces, and Dissemination).[3]

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[2] An interpretation of these results is that the people training to fight this particular battle (Korea) feel they will be working in a target-rich environment and thus put little value on identifying more important targets.

[3] These increased system capabilities could result from the addition of better airborne capabilities.

With these changes, the theoretical prediction is that 59% of the immediate targeting opportunities would be exploited.

Tradeoffs in the contribution of two factors to an outcome can be assessed by looking at a graph of theoretical predictions. This is shown in Fig. 8 for the facility operability and dissemination factors of Figs. 5-6. It can be seen from this graph that the prediction (on the y-axis) is about the same for a dissemination level of 10% and a Facility operability level of 90% as for a dissemination level of 60% and a Facility operability level of 30%. Other tradeoffs between these factors can be assessed by drawing horizontal lines through the theoretical curves. For graphic tradeoffs among 3 factors, a graph for two factors such as that shown in Fig. 8 would be plotted at each level of the third factor. Graphic procedures for evaluating tradeoffs would be especially useful in situations where the decision about which system changes to make involve only a few system factors.

The actual primitive factor levels selected in an evaluation would be determined from such things as systems being entertained for purchase, production, development, and/or present capability levels.

VI. SUMMARY REMARKS

Illustrations in this paper have been in the Air Force command and control arena, since that is the problem domain to which the approach has been applied. However, it is hoped that the demonstrations served to illustrate how the approach could be applied to a wide variety of systems. System evaluations obtained using this approach could be used to aid decisionmakers in assessing operational consequences of alternative system capabilites, since they serve to pinpoint where in the system changes make a difference. Further it aids in decisions about what research to support as well as equipment to develop, produce, and/or purchase.

The major advantage of using the STF approach to analyze systems is that the tested STF provides a validity base for conclusions about what affects system outcomes. This testability feature is absent from a number of commonly used approaches to analyzing systems described earlier. However, it is vital feature if conclusions are to be credible.

REFERENCES

1. Alexander, J. M. and Saaty, T. L. The forward and backward processes of conflict analysis, Behavioral Science, 22 (1977),

2. Anderson, N. H., Functional measurement and psychophysical judgment, Psychological Review, 77 (1970), 153-170.

3. Anderson, N. H., Algebraic rules and psychological measurement, American Scientist, 21 (1979), 201-215.

4. Anderson, N. H., Foundations of Information Integration Theory, New York: Academic Press, 1981.

5. Birnbaum, M. H., The nonadditivity of personality impressions, Journal of Experimental Psychology, 102 (1974) 543-561 (monograph).

6. Birnbaum, M. H., Intuitive numerical prediction, American Journal of Psychology, 89 (1976), 417-429.

7. Birnbaum, M. H., Differences and ratios in psychological measurement. In N. J. Castellan and Restle (Eds.), Cognitive Theory (Vol. 3), Hillsday, New Jersey: Erlbaum, 1978.

8. Birnbaum, M. H., Comparison of two theories of "ratio" and "difference" judgments, Journal of Experimental Psychology: General, 109 (1980) 304-319.

9. Birnbaum, M. H., Controversies in psychological measurement. In B. Wegener (Ed.) Social Attitudes and Psychophysical Measurement, Hillsdale: Lawrence Erlbaum Associates, 1982.

10. Birnbaum, M. H. and Mellers, B. A., Measurement and the mental map, Perception and Psychophysics, 23 (1978) 403-408.

11. Birnbaum, M. H. and Stegner, S. E., Source credibility in social judgment: Bias, expertise, and the judge's point of view, Journal of Personality and Social Psychology, 37 (1979), 48-74.

12. Birnbaum, M. H. and Stegner, S. E., Measuring the importance of cues in judgment for individuals: Subjective theories of IQ as a function of heredity and environment, Journal of Experimental Social Psychology, 17 (1981), 159-182.

13. Birnbaum, M. H. and Veit, C. T., Scale convergence as a criterion for rescaling: Information integration with difference, ratio, and averaging tasks, Perception and Psychophysics, 15 (1974), 7-15. (a)

14. Birnbaum, M. H. and Veit, C. T., Scale-free tests of an additive model for the size-weight illusion, Perception and Psychophysics, 16 (1974), 276-282. (b)

15. Chandler, J. P., STEPIT--Finds local minima of a smooth function of several parameters, Behavioral Science, 14 (1969), 81-82.

16. Levin, I. P., Information integratin in numerical judgments and decision processes, Journal of Experimetal Psychology: General, 104 (1975), 39-53.

17. Gardiner, P. C. and Edwards, W. Public values: Multiattribute-utility measurement for social decision making. In M. F. Kaplan and S. Schwartz (Eds.), Human Judgment and Decision Processes. New York: Academic Press, 1975.

18. Kelly, C. W., Andriole, S. J., and Daly, J. A. Computer-based Bayesian information processing. Proceedings of the International Conference on Cybernetics and Society, Part II, 1978.

19. Krantz, D. H., Measurement structure and psychological laws, Science, 175 (1972), 1427-1435.

20. Krantz, D. H., Luce, R. D., Suppes, P., and Tversky, A., Foundations of Measurement, New York: Academic Press, 1971.

21. Krantz, D. H., and Tversky, A., Conjoint-measurement analysis of composition rules in psychology, Psychological Review, 78 (1971), 151-169.

22. Martin, A. W., Bresnick, T. A., and Buede, D. M., Evaluation of command and control centers. Technical Report TR 81-3-328, McLean, Va.: Decisions and Designs, Inc., 1981.

23. Miller, G. A. The magical number seven, plus or minus two; Some limits on our capacity for processing information. The Psychological Review, 1956, 63, 81-97.

24. Norman, K. L., A solution for weights and scale values in functional measurement. Psychological Review, 1976, 83, 1, 80-84.

25. O'Conner, M. F. Procedures for assessing the value of command and control capabilities. Technical Report 77-4, McLean, Va.: Decisions and Designs, Inc., 1977.

26. Pirie, R. B., Frisvold, G. A., and Bresnick, T. A. Application of advanced decision-analytic technology to rapid deployment joint ask force problems. Technical Report TR 81-7-328.13, McLean, Va.: Decisions and Designs, Inc., 1981.

27. Poulton, E. C. The new psychophysics: Six models for magnitude estimation. Psychological Bulletin, 69 (1968), 1-19.

28. Saaty, T. L. A scaling method for priorities in hierarchical structures, Journal of Mathematical Psychology, 15 (1977), 234-281.

29. Savage, C. W., Introspectionist and behaviorist interpretations of ratio scales of perceptual magnitudes, Psychological Monograph, 80 (1966), 1-32.

30. Shepard, R. N., On the status of "direct" psychological measurement. In Savage (ed.), Minnesota Studies in the Philosophy of Science, Vol. IX, Minneapolis: University of Minnesota Press, 1976.

31. Stevens, S. S., On the theory of scales and measurement, Science, 103 (1946), 677-680.

32. Stevens, S. S., On the psychophysical law, Psychological Review, 64 (1957), 153-181.

33. Stevens, S. S. and Galanter, E. H. Ratio scales and category scales for a dozen perceptual continua, Journal of Experimental Psychology, 54 (1957), 377-411.

34. Treisman, M., Sensory scaling and the psychophysical law, Quarterly Journal of Experimental Psychology, 16 (1964), 11-22.

35. Veit, C. T., Ratio and subtractive processes in psychophysical judgment, Journal of Experimental Psychology, 107 (1978), 81-107.

36. Veit, C. T., Analyzing "ratio" and "difference" judgments: A reply to Rule and Curtis, Journal of Experimental Psychology: General, 109 (1980), 301-303.

37. Veit, C. T., Callero, M. Subjective transfer function approach to complex system analysis, The Rand Corporation, R-2719-AF, 1981.

38. Veit, C. T., Callero, M., and Rose, B. J., Demonstration of the subjective transfer function approach applied to Air-Force-Wide Mission Area Analysis, The Rand Corporation, N-1831-AF, 1982.

39. Veit, C. T., Callero, M., and Rose, B. J., Introduction to the STF function approach to analyzing systems. The Rand Corporation, R-3021-AF, (forthcoming).

40. Veit, C. T. Rose, B. J., and Ware, J. E., Effects of physical and mental health on health-state preferences, Medical Care, 20 (1982), 386-401.

41. Waddington, C. H., Tools for Thought, New York: Basic Books, Inc., 1977.

TABLES AND FIGURES

Table 1

Definitions for C2 Factors and Outcomes
Shown in Figures 1 and 2

Experimental Unit 1 (Immediate Targeting Experts)

Judged Outcome: The percent of force application opportunities that could be exploited in a timely manner

Factor Definitions	Factor Levels
Target Identification: The percent of important force elements identified.	90% 60% 30% 10%
Facility Operability: The percent of immediate targeting activities that can be supported by the facility.	90% 60% 30% 10%
Alert Forces: Status of the Alert Forces accessible in the C2 facility	90% 60% 30% 10%
Airborne Forces: Status of the airborne forces accessible in the C2 facility	90% 60% 30% 10%
Weather: The currency of the reliable weather information	15 min., 1 hr, 3 hrs, 12 hrs.
Dissemination: The percent of the forces that can be tasked in a timely manner	90% 60% 30% 10%

Experimental Unit 2 (Targeting Experts)

Judged Outcome: The percent of important enemy targets that could be identified in a timely manner

Factor Definitions	Factor Levels
Vehicle Location/Classification: The ability of sensor systems to locate and classify enemy vehicles.	Locate and Classify in all weather. Locate (not classify) in all weather. Locate and classify in clear weather.

Vehicle Coverage: The percent of enemy vehicles that have been observed.	90%, 60%, 30%, 10%
Vehicle Currency: The time interval between the observation of enemy vehicles and the data's availability fo processing.	5 min., 15 min., 30 min., 1 hr.
Processing: The means by which enemy vehicle and emitter information is interpreted.	Fully computerized interpretation. Human uses computer to graphically display info.; human interpretation. Human uses computer to sort textual info; human interpretation. Human sorts hard copy, textual info; human interpretation.
Emitter Location Accuracy: The accuracy with which enemy emitters are located.	10m, 100m, 1000m
Emitter Coverage: The percent of the enemy emitters that have been observed.	90%, 60%, 30%, 10.
Emitter Currency: The time interval between the observation of emitters and the data's availability for processing.	5 min., 15 min., 30 min., 1 hr.

TABLE 2

POSSIBLE STFs

A.

NONINTERACTIVE FUNCTIONS

$$r = \sum_{i=1}^{f} w_i s_i$$

Additive

$$r = \frac{\sum_{i=1}^{f} w_i s_i}{\sum_{i=1}^{f} w_i}$$

Simple averaging

$$r = \frac{w_0 s_0 + \sum_{i=1}^{f} w_i s_i}{w_0 + \sum_{i=1}^{f} w_i}$$

Averaging with initial impression

B.

INTERACTIVE FUNCTIONS

Multiplicative combination of factors

$$r = \frac{w_0 s_0 + \sum_{i=1}^{f} w_i s_i}{w_0 + \sum_{i=1}^{f} w_i} + \omega\,(s_{max} - s_{min})$$

Range

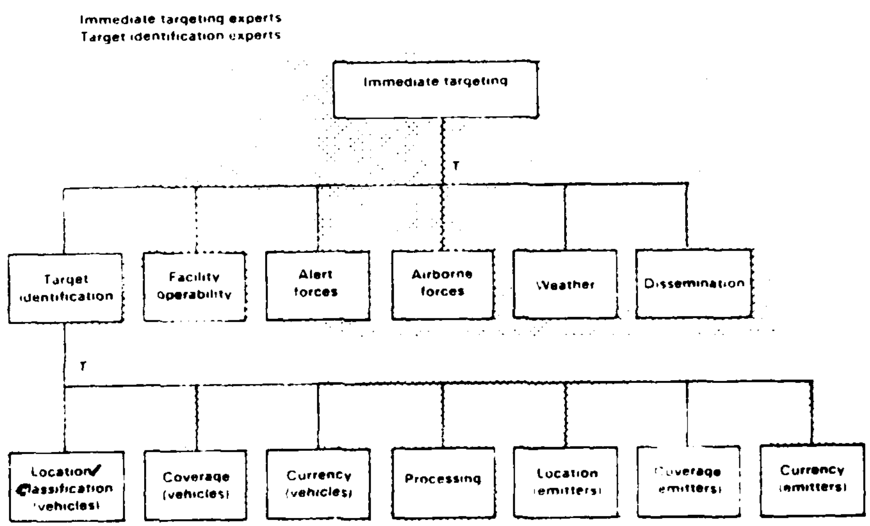
$$r = \frac{w_0 s_0 + \sum_{i=1}^{f} w_{I_i} s_{I_i}}{w_0 + \sum_{i=1}^{f} w_{I_i}}$$

Differential weight

Rand

FIG. 1

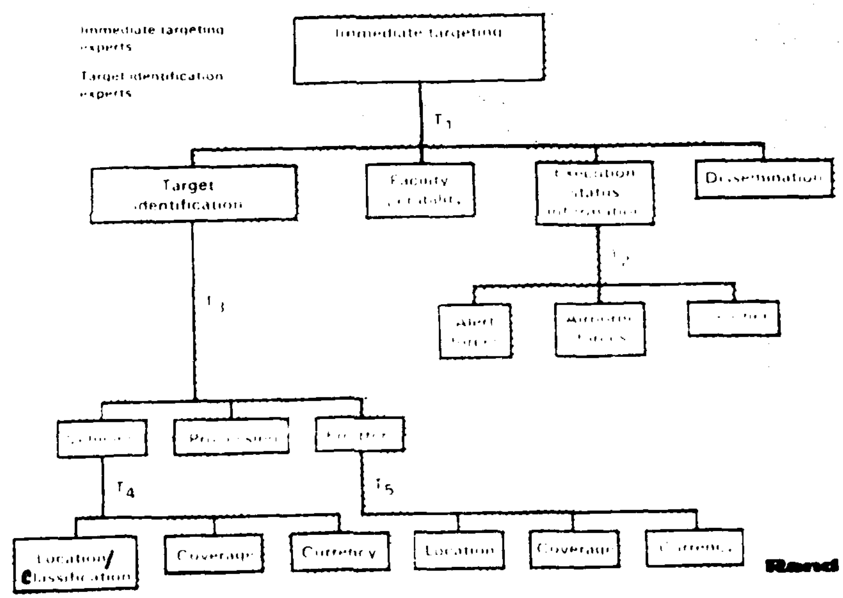
HYPOTHESIZED IMMEDIATE TARGETING STRUCTURE



Rand

FIG. 2

HYPOTHESIZED IMMEDIATE TARGETING STRUCTURE



FINAL STRUCTURE AND STFs

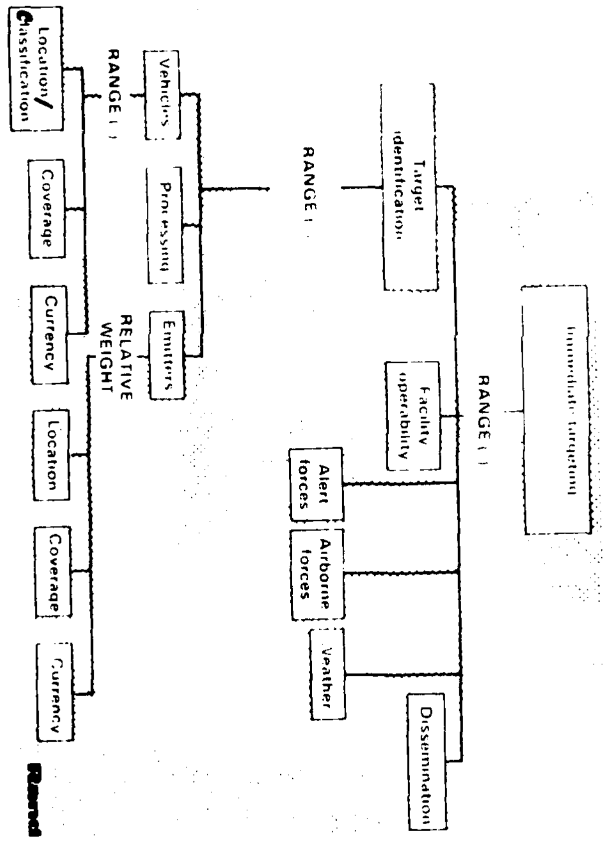
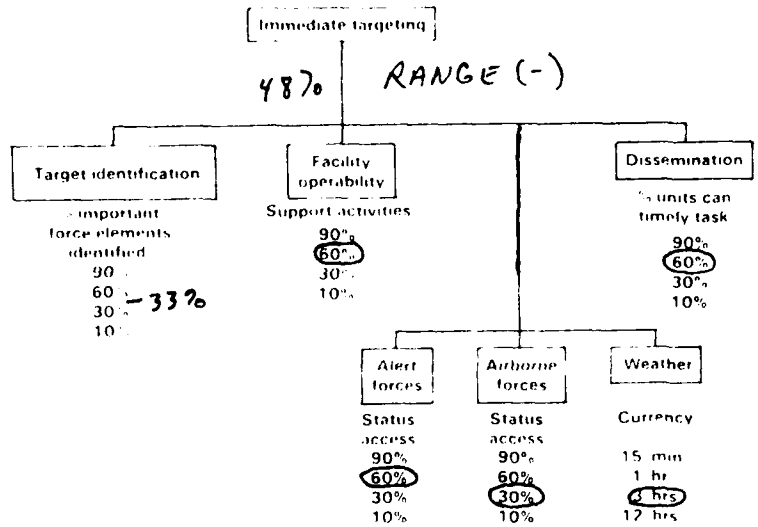
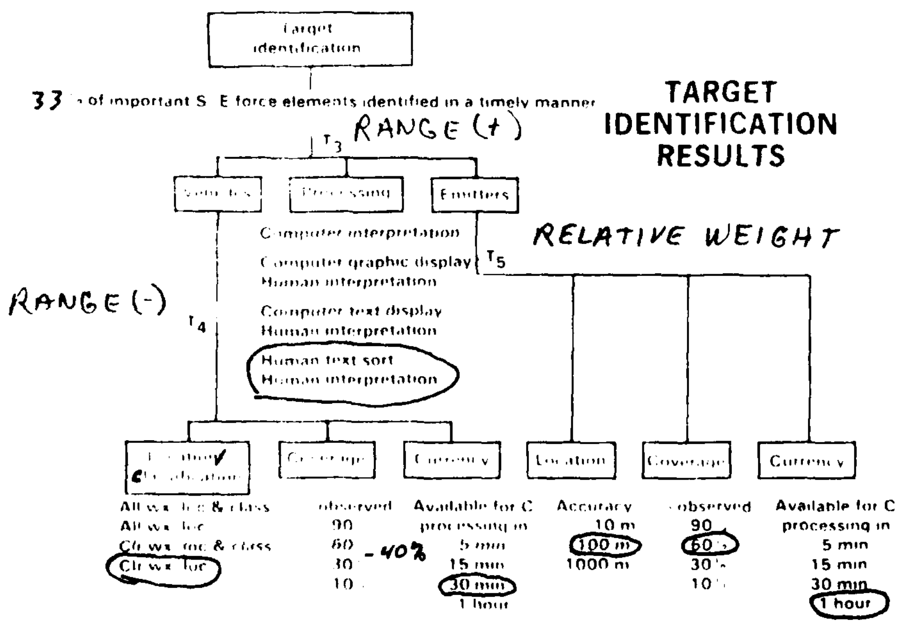


FIG. 3

FIG. 4

IMMEDIATE TARGETING RESULTS

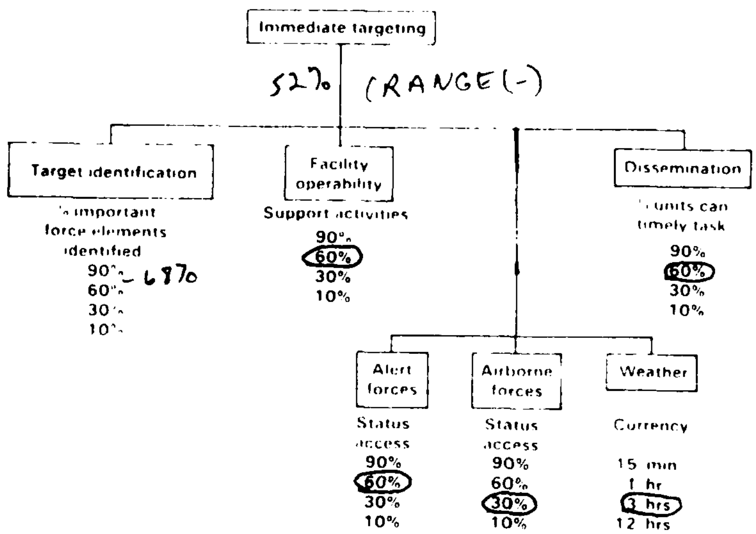




TARGET IDENTIFICATION RESULTS

FIG. 5

IMMEDIATE TARGETING RESULTS



TARGET IDENTIFICATION RESULTS

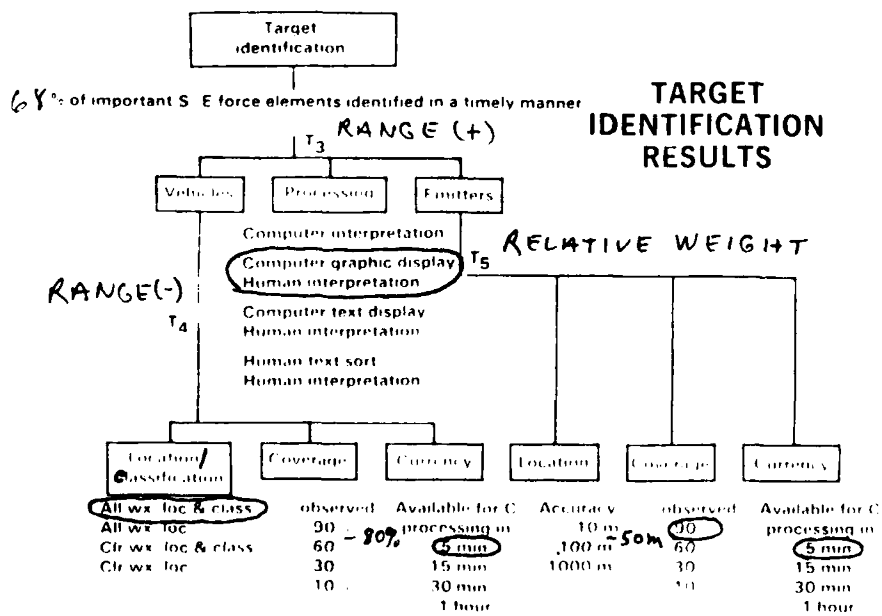
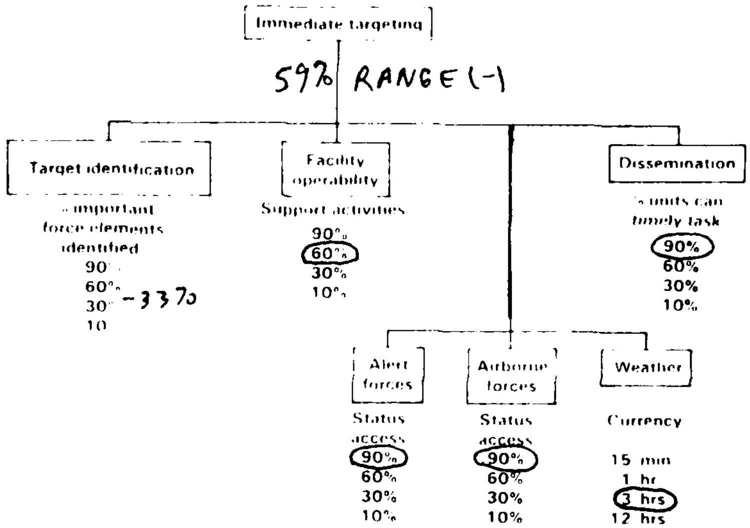
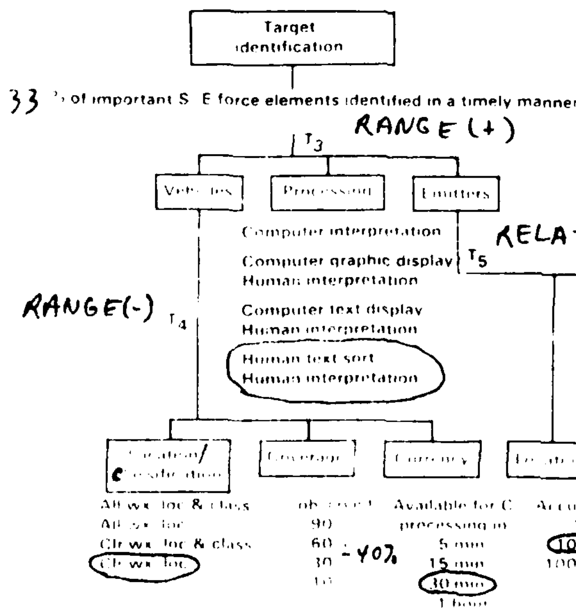


FIG. 6

IMMEDIATE TARGETING RESULTS



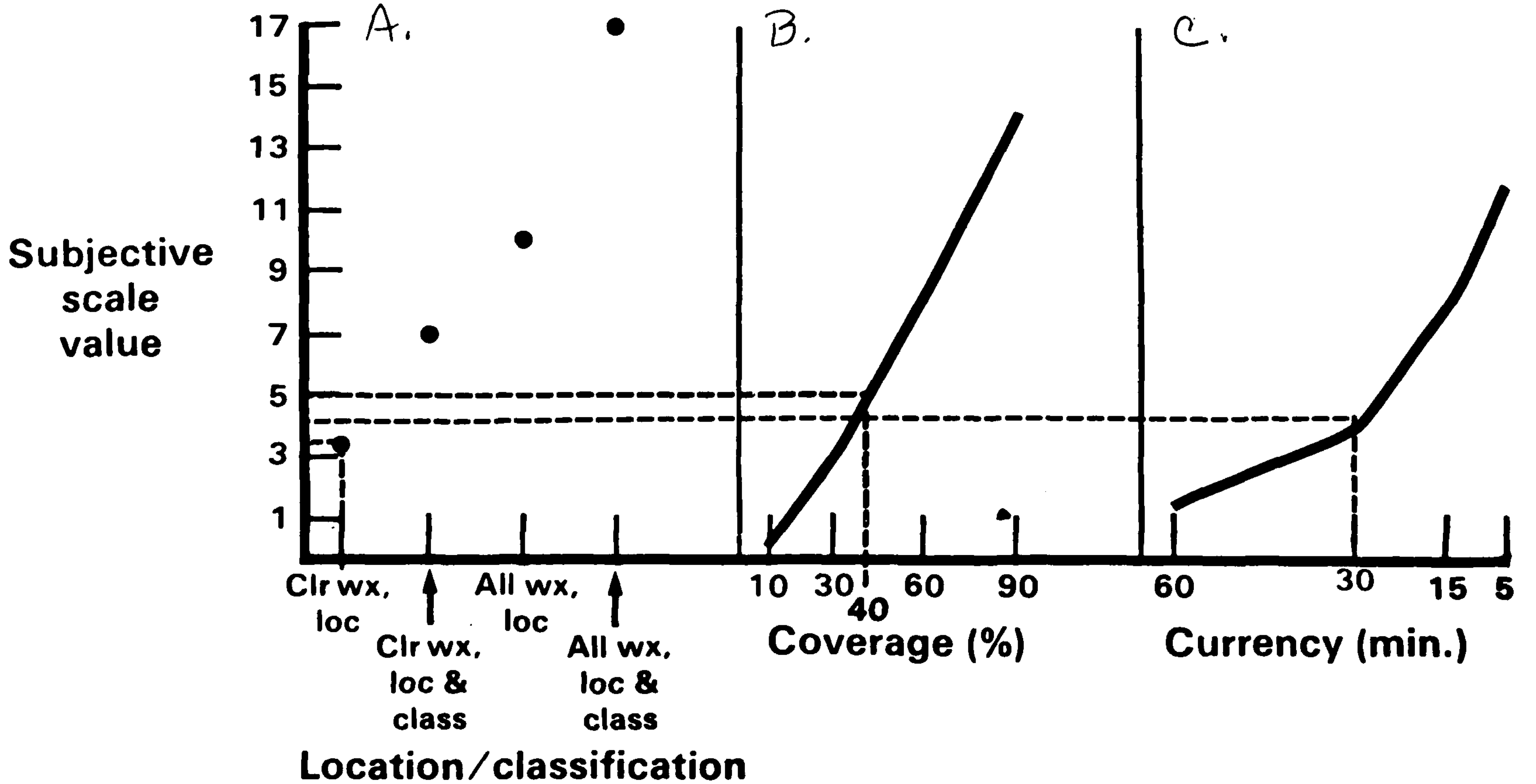


TARGET IDENTIFICATION RESULTS

FIG. 7

SUBJECTIVE SCALE VALUES FOR ENEMY VEHICLE FACTORS

$$r = \frac{W_O S_O + W_L S_L + W_C S_C + W_T S_T}{W_O + W_L + W_C + W_T} + \omega(S_{max} - S_{min})$$



Rand

FIG. 8

THEORETICAL PREDICTIONS